NOTES & UNIQUE PHENOMENA

PORTABLE HYPERSPECTRAL TUNABLE IMAGING SYSTEM (PHyTIS) FOR PRECISION AGRICULTURE

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Abstract

Hyperspectral remote sensing can provide contiguous spectra of scenes made up of dozens to hundreds of narrow wavebands, across the visible and near-infrared portions of the spectrum. This emerging technology provides spatial and spectral information that can be acquired simultaneously. Presented here for use in agricultural research is the Portable Hyperspectral Tunable Imaging System (PHyTIS). It is a computer-controlled, liquid-crystal tunable filter, digital imaging system designed to extract spectra of typical agronomic scene components (endmembers) such as sunlit and shaded leaves and soil for spectral mixture analysis. Results from a scene acquired in a cotton (*Gossypium hirsutum* L.) field showed that scene components could be successfully unmixed and area of each quantified. Image processing and hyperspectral remote sensing can identify endmembers to quantify crop biophysical parameters, to derive fractional cover maps, and could be used as inputs to plant, soil, and evapotranspiration models.

Remote sensing has been shown to be a valuable tool in mapping and quantifying within-field biophysical variations for use in research and management (Moran et al., 1997). One emerging technology in remote sensing applications to agriculture is hyperspectral remote sensing. This technology can provide a contiguous spectrum of dozens to hundreds of narrow wavebands, across the visible and near- and midinfrared portions of the spectrum. If the hyperspectral system is an imaging system, then X, Y, and Z information can be acquired, where X and Y locate a position within an image and Z is the spectral waveband. Thus, contiguous spatial and spectral information can be gathered simultaneously.

Imaging hyperspectral remote sensing combined with image-processing techniques can allow identification and quantification of scene components. Spectral responses to various biophysical parameters such as N or water stress, whether imposed or naturally occurring, can be measured and their locations in a field identified. Additionally, the fractional area within a scene of soil, green plants, shade, wet soil, dry soil, etc., can be extracted from hyperspectral imagery (Adams and Smith, 1986; Sabol et al., 1992). These data can be used as inputs to models requiring, for example, ground cover or fraction sunlit and shaded soil. Many image-processing techniques could be used to extract relevant information from the imagery, including derivative analysis, principal-component (PC) analysis, and spectral mixture analysis (SMA). Briefly, linear spectral unmixing (LSU) is based on the assumption that each pixel in an image is a physical mixture of multiple components (endmembers) and the spectrum of each mixed pixel is a linear combination of the endmember reflectance spectra (Tompkins et al., 1997). Spectral mixture analysis also assumes that a small number of spectra representing the endmembers can describe most of the spectral variation in a pixel and can be used to *unmix* the pixels and determine the relative fractional abundance of each endmember on a per-pixel basis. In precision agriculture, this approach could allow for discrimination of plant stresses, nutrient status, etc., as well as measurement of area occupied (fractional abundance) by each component through identification of unique spectral features or differences in shapes of the spectral curves. Here, spectral unmixing will be discussed as an analysis tool for precision agriculture with promising potential.

This note describes an imaging device dubbed PHyTIS, or Portable Hyperspectral Tunable Imaging System, built for use in agricultural fields to derive spectral scene components (endmembers) for use principally in SMA of canopy-level scenes although leaf-level analysis is also possible.

Materials and Methods

PHyTIS Hardware and Deployment

The PHyTIS package is composed of two liquid-crystal tunable filters (Varispec filters, Cambridge Research Instrumentation, Woburn, MA, USA), one transmissive to visible light (400–720 nm) and the other principally to near-infrared (NIR) radiation (650–1100 nm). These are contained inside an optically sealed *switch* box and moved back and forth in front of the lens through a computer-controlled motor. The filter switchbox also has a closed setting allowing acquisition of dark-image cubes. The filters are factory-set to measure 10-nm-wide wavebands (full width half maximum), but the waveband centers can be electronically tuned to vary by as little as 1.25 nm. Typically, waveband centers are set to 5- or 10-nm resolution. The filters can record up to 128 bands each. A 12-bit, 1360- by 1036-pixel, piezo-electrically cooled, firewire, monochrome digital camera (model Retiga EX, Quantitative Imaging Corp., Burnaby, BC, Canada) is attached be-

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Abbreviations: DN, digital numbers; LSU, linear spectral unmixing; NIR, near infrared; PC, principal component; RMSE, root mean square error; SMA, spectral mixture analysis.

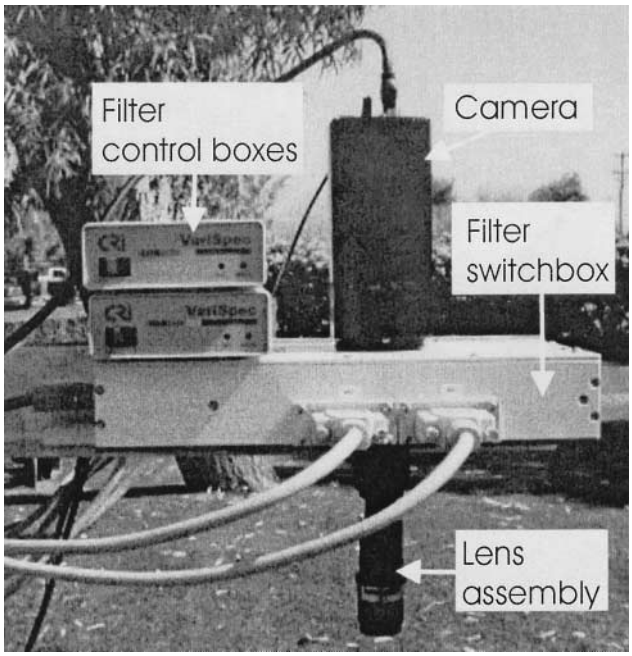

Fig. 1. Portable Hyperspectral Tunable Imaging System (PHyTIS). See text for component details.

hind the filters with a lens assembly placed in front (Fig. 1). The lenses can be focused from 0 m to infinity. Field of view is 15 by 20 degrees. Filter switching, camera integration time, and frame rate are synchronized so that as the filter steps through each preset waveband, an image is acquired. Thus, an *X*, *Y*, *Z* image cube is built up and stored to disk when complete. The system is controlled by a *wearable* computer (model Mobile Assistant V, Xybernaut, Fairfax, VA, USA) with a touch-screen display and custom software written specifically for controlling this camera system. The operator can specify all relevant parameters, including waveband centers, binning, and integration times. Binning refers to averaging the signal from square blocks of pixels. The entire system can be carried into a field and set up by one or two people. The filter switch box, camera, and lens assembly weigh about 5 kg. It is currently deployed either on a tripod with a boom such that the system can be raised to about 2.5 m above the soil surface or on a longer boom over a fixed site that allows deployment about 8 m above the soil. Deployment from an aircraft is currently being investigated.

The amount of light captured in the final image is an interplay of camera sensitivity, pixel binning, integration time, lens aperture, and filter transmissivity. Camera sensitivity, pixel binning, and integration time are analogous to film sensitivity to wavelength, film speed, and shutter speed, respectively, in conventional photography. The PHyTIS can provide binning up to 4 by 4 pixels. Increased binning decreases the effective spatial resolution of the image but increases the light captured in a linear relation with the number of pixels binned. The NIR filter is less transmissive than the visible filter, so in order for the camera to receive the same amount of light, the integration times will increase in the NIR compared to the visible. Thus, integration times for a typical scene for the most light-sensitive band (705 nm) with the visible filter and one of the least-sensitive NIR filter bands (1000 nm) set at Binning Level 2 are 0.9 and 63 ms, respectively. Examples of total acquisition time for a cube composed of images from 400 to 1100 nm at 10-nm intervals are 17 s at Binning Level 4 and 32 s at Binning Level 2. Pixel resolution at Binning Level 2 is 0.53 mm when the camera is 1 m above the target.

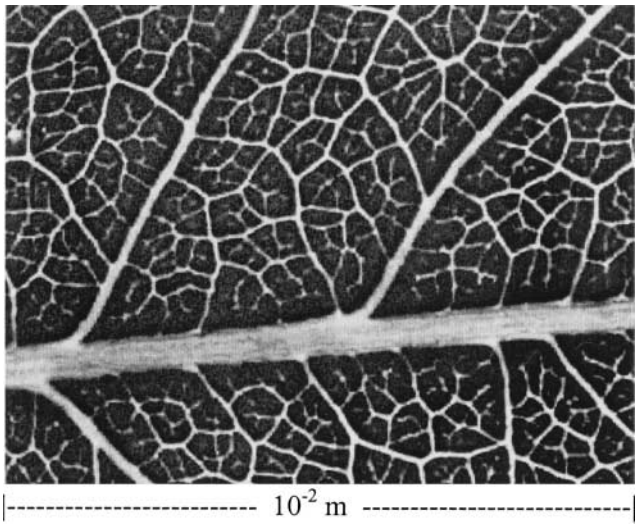

Fig. 2. Transmission of diffuse sunlight through leaf at 700 nm showing fine details.

The PHyTIS package can be used for subleaf to canopy-scale studies. Figure 2 shows an image of transmission of diffuse sunlight through a leaf at 700 nm. Pixel size at this full resolution was about 1.5 by 10^{-5} m. This image is shown to demonstrate the system's capabilities although the principal use of PHyTIS is at the plant/canopy scale where sunlit and shaded leaves and soil are present.

The camera system was tested in research cotton fields located at The University of Arizona Maricopa Agricultural Center in Maricopa, AZ. It was deployed in the field at various times during the season to acquire images of canopy components. Figure 3a shows an example of one image acquired at 800 nm and used here for analysis.

To allow conversion of imagery collected in digital numbers (DN) to reflectance, reference- and dark-image cubes were acquired near the time of the actual target acquisition. The PHyTIS package was leveled and pointed straight down at a level Spectralon (Labsphere, North Sutton, NH, USA) 99% reflectance panel such that the panel occupied the entire scene. The brightness level was measured with the camera automatically setting maximum pixel values for each waveband based on the panel brightness and tolerance set beforehand by the operator. This ensured that the images would not saturate beyond the 4095 DN maximum. Then, a reference-image cube was acquired of the Spectralon panel. Immediately afterwards, a dark-image cube was acquired by setting the switchbox to the closed position and using the same settings used for the reference panel acquisition. The dark image was later subtracted to remove system noise. Dark-pixel values ranged from 20 to 60 DN, or about 1% of the system maximum. Every few minutes, the operator returned to the reflectance panel to acquire another set of reference and dark images.

Image Processing

The remote sensing analysis software ENVI (Research Systems, Boulder, CO, USA) was used for all image processing. Once image cubes were converted to reflectance, endmembers were identified in the scenes using a tool in ENVI called Minimum Noise Fraction. This is a two-step procedure that segregates the noise in the data and then performs a standard PC analysis (Research Systems, 2000). The PC analysis transforms the data such that the spectral features that contain the most information are in the first few bands; typically these relate to variations in overall scene brightness. For the pur-

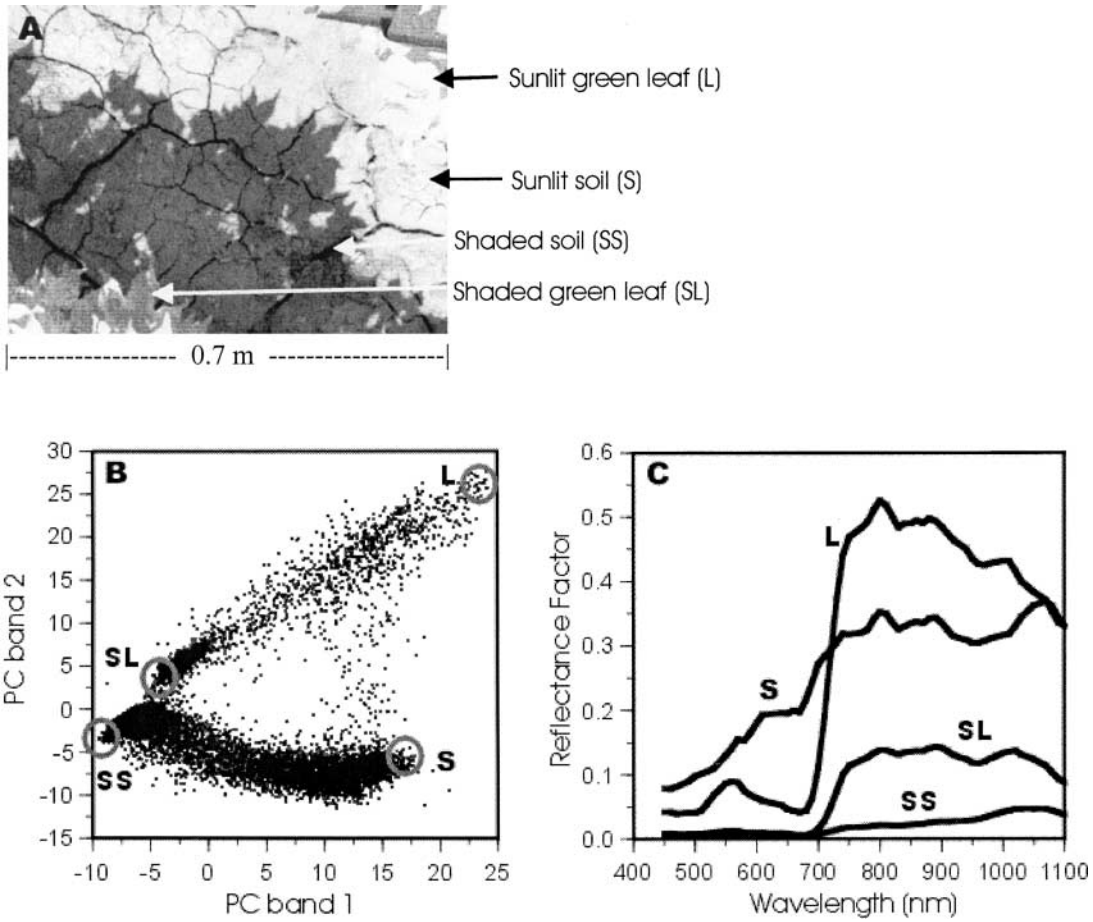

Fig. 3. Endmember selection process. (A) Scene (at 800 nm) used for analysis and showing the physical locations of endmember pixels selected by choosing spectral regions indicated by letters and circles in Fig. 3B, (B) endmembers selected by plotting Principal-Component (PC) Bands 1 and 2 and choosing pixels within the circles shown, and (C) spectra of endmembers selected from Fig. 3B.

poses of identifying shaded and sunlit components, the first two bands are used to locate the scene components in the images. In Fig. 3a, 72% of the scene information is in these two bands, according to their eigenvalues. When the first two PC bands are plotted (Fig. 3b), the endmembers can be selected as the end points of the data clouds (hence the term, endmember). In hyperspectral data of agricultural fields, typically there will be a vegetation line and a soil line. The extreme values along a line represent the brightest and darkest of these scene components. Thus, the four components selected here, sunlit and shaded leaves and sunlit and shaded soil, were identified and the spectra extracted (Fig. 3c). Figure 3a shows the locations in the scene of the points selected interactively from the PC plot in Fig. 3b. The interactive nature of the procedure permits selection of areas in either the scene or plot to be shown in both windows on the computer screen with colored points, allowing verification of the components. Once the endmembers were selected, a spectral library was created containing the endmembers of interest.

The scene representing the image cube in Fig. 3a was spatially resampled to reduce computational requirements. It was then unmixed with the endmembers in the spectral library using the LSU routine in ENVI resulting in five fractional abundance images (Fig. 4a–4e). The unmixing routine outputs one image for each input endmember plus a root mean square error (RMSE) image (Fig. 4). The LSU routine was modified to account for variable endmembers across the scene as originally described in Roberts et al. (1998) and adapted for precision agriculture by Fitzgerald et al. (2004). To measure the area of the scene occupied by these different fractions, thresholds were chosen based on visually selecting values that match the shaded and sunlit leaves and soil in the scene. The number of pixels in each region was divided by the total pixels in the scene to calculate fractional areas (Table 1). A false-color image combining three of the four fraction images represents these regions well (Fig. 4f).

Since spectral unmixing results in a continuum of fractional values for the scene components, it is necessary to choose threshold values to classify them into discrete areas. Here, this is done manually to illustrate the point that the major components in the scene can be selected by unmixing, but more sophisticated or automated procedures might be possible.

Results

The scene selected for analysis (Fig. 3a) contained the main components that make up most agronomic scenes—sunlit green leaves, sunlit soil, shaded green leaves, and shaded soil. The bright pixels in Fig. 4a through 4e show the capability of SMA to extract these various scene components from the imagery. In each panel, the bright areas correspond to those pixels with greater fractions of the endmember indicated. The RMSE image is calculated by comparing the spectra from each pixel in the original image cube to the pixel spectra in the final modeled spectra. The RMSE image shows greatest error along leaf shadow edges due to slight movement from

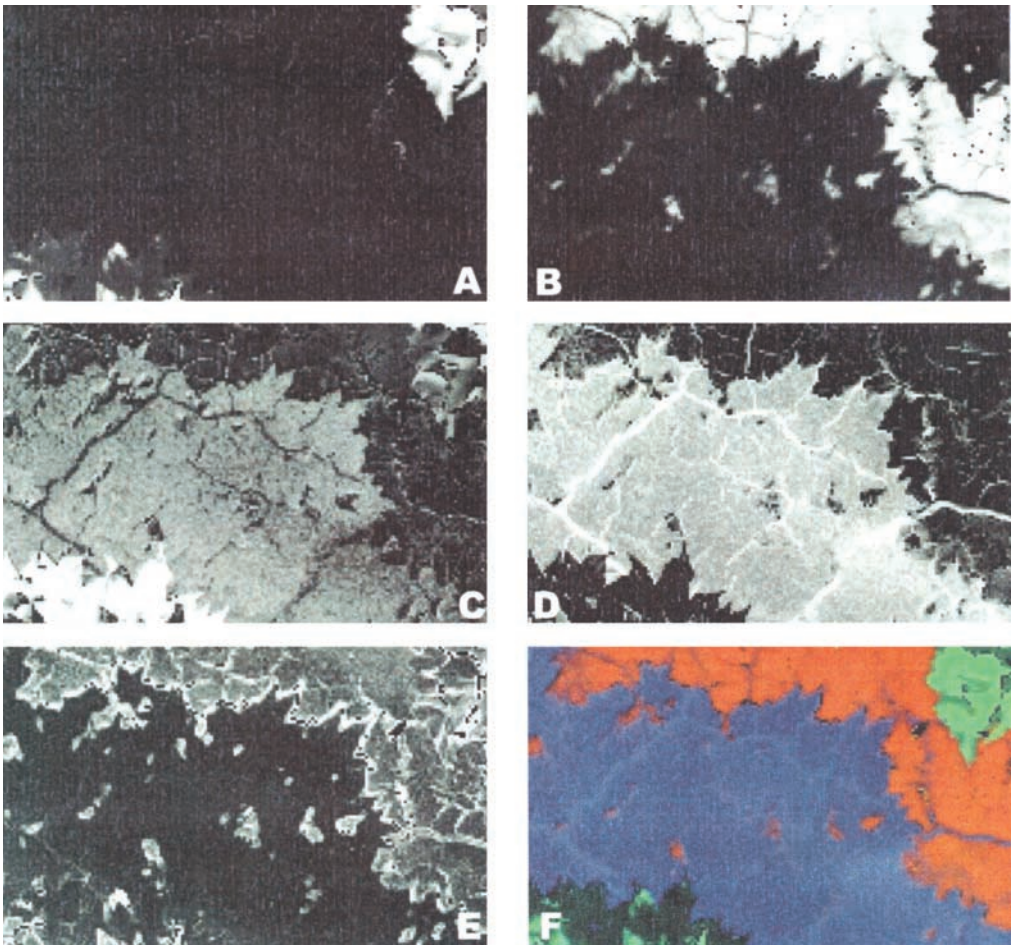

Fig. 4. Unmixed abundance fraction images, root mean square error (RMSE) image, and false-color composite. Dark to bright pixels represent a continuum of pixel values from 0 to 1. (A) Sunlit green-leaf fraction, (B) sunlit soil fraction, (C) shaded green-leaf fraction, (D) shaded soil fraction, (E) RMSE image, and (F) composite color fraction image: red = sunlit soil, green = sunlit green leaf, blue = shaded soil, and dark green = shaded green leaf.

wind. It is reasonable to expect that these areas did not correspond as closely to the reference endmembers in the spectral library. The mean RMSE for the entire scene was equal to 0.007, well within system noise levels. No pixel had an RMSE greater than 0.03.

In Fig. 4f, the four scene components are clearly depicted with the sunlit leaves colored green, the sunlit soil red, and the shaded soil blue. The shaded leaves show up as a darker green. Thus, scene fractional abundances can be represented in imagery and calculated in tabular form (Table 1). Fraction values could be correlated with measured plant or soil characteristics to derive relationships between the imagery and biophysical parameters. Simultaneous measures of shaded and sunlit soil, for example, could be used as area-based inputs to model soil evaporation. Fractional cover of sunlit and shaded leaves could be used as inputs to studies of canopy-scale photosynthesis, C accumulation, and nutrient status, or to understand other biophysical processes. Although analysis of the scene here shows a fine-scale image, the endmembers derived from scenes like this one could be used to unmix field-scale images to quantify fractions across fields. This is certainly not straightforward but will be the subject of research performed using the PHyTIS package.

Table 1. Fractional abundance of scene components in Figure 4.

Endmember	Scene fraction
Sunlit green leaf	0.047
Sunlit soil	0.292
Shaded green leaf	0.059
Shaded soil	0.606

Discussion

Spectral mixture analysis has been used to process imagery from ecological studies for a number of years, and the procedure is well documented beginning with Adams and Smith (1986) and more recently in Okin et al. (2001) (and references therein). Traditional vegetation indices, such as NDVI, are affected by soil background color (Huete et al., 1985) and thus are difficult to interpret under partial-canopy conditions. Spectrally unmixed fractions could allow for differentiation of the soil background and have the advantage of explicitly including shade as a component that can also be removed from analysis or used as another variable. Very little has been published about comparing fractional abundances with vegetation indices, but the shade fraction has been shown to correlate better to biophysical

canopy information in forests and potato (*Solanum tuberosum* L.) crops than traditional vegetation indices (Peddle et al., 1999, 2001). An advantage of spectral unmixing is that each pixel in a scene is assigned a fractional value for each of the input endmembers. Thus, a pixel selected from a mostly soil-dominant section of a field might contain 0.6 sunlit soil, 0.2 sunlit leaves, 0.1 shaded soil, and 0.1 shaded leaves. In a closed canopy, the proportions might be 0.85 leaves and 0.15 shaded leaves. This provides a direct measure of a physically based parameter rather than an arbitrary and difficult-to-interpret value such as that produced by PC analysis or a discrete value output from conventional classification approaches. Thus, unmixing provides values that can either be used to classify an image using threshold values (as done here) or used directly in regressions and models to relate to ground-measured parameters.

Nonimaging field spectrometers have the capability of measuring canopy components across the visible and NIR portions of the spectrum and can provide detailed spectral data sets at single points in the field. With an imaging hyperspectral system, a researcher can additionally measure fractional cover directly for use as *ground truth* for the unmixing procedure, reveal endmembers not readily apparent in the scene at the time of measurement through use of advanced image-processing techniques, measure multiple-shaded components and spectra of components too small to capture with a nonimaging device, characterize leaf structure, and potentially quantify three-dimensional spatial variations, including bidirectional reflectance distribution factor, leaf angle, and the physical orientation and placement of leaves within a canopy.

Conclusions

The PHyTIS package can record hyperspectral imagery at subleaf to canopy scales from which spectral endmembers can be collected. Future deployment will allow acquisition of field-level imagery. The endmembers can be used in SMA to unmix hyperspectral imagery for identifying and locating stresses and nutrient status as well as measuring fractional abundances useful as inputs to spatially explicit plant and soil models or as correlations to biophysical parameters such as ground cover. Future work will include developing relationships among the ground-collected endmember spectra, field-level imagery, and important biophysical parameters such as leaf area index (LAI), ground cover, N status, evapotranspiration, and water stress.

Acknowledgments

Zedec Technologies, Morrisville, NC, USA, integrated the system hardware and developed software control.

References

Adams, J.B., and M.O. Smith. 1986. Spectral mixture modeling: A new analysis of rock and soil types at the Viking Lander 1 Site. J. Geophys. Res. 91:8098–8112.

Fitzgerald, G.J., S.J. Maas, and W.R. DeTar. 2004. Spider mite detection and canopy component mapping in cotton using hyperspectral imagery and spectral mixture analysis. Precis. Agric. 5:(in press).

Huete, A.R., R.D. Jackson, and D.F. Post. 1985. Spectral response of a plant canopy with different soil backgrounds. Remote Sens. Environ. 17:37–53.

Moran, M.S., Y. Inoue, and E.M. Barnes. 1997. Opportunities and limitations for image-based remote sensing and precision crop management. Remote Sens. Environ. 61:319–346.

Okin, G.S., D.A. Roberts, B. Murray, and W.J. Okin. 2001. Practical limits on hyperspectral vegetation discrimination in arid and semiarid environments. Remote Sens. Environ. 77:212–225.

Peddle, D.R., S.P. Brunke, and F.G. Hall. 2001. A comparison of spectral mixture analysis and ten vegetation indices for estimating boreal forest biophysical information from airborne data. Can. J. Remote Sens. 27:627–635.

Peddle, D.R., A.M. Smith, C. Ivie, M. Bullock, and S. Russell. 1999. Spectral mixture analysis of agricultural crops under different irrigation regimes: Scene fraction validation in potato plots. *In* Proc. Int. Airborne Remote Sensing Conf. and Exhibition, 4th, and Canadian Symp. on Remote Sensing, 21st, Ottawa, ON, Canada. 21–24 June 1999 [CD-ROM]. Environ. Res. Inst. of Michigan, Ann Arbor.

Research Systems. 2000. ENVI user's guide. Release 3.5.1. Res. Syst., Boulder, CO, USA.

Roberts, D.A., M. Gardner, R. Church, S. Ustin, G. Scheer, and R.O. Green. 1998. Mapping chaparral in the Santa Monica mountains using multiple endmember spectral mixture models. Remote Sens. Environ. 65:267–279.

Sabol, D.E., J.B. Adams, and M.O. Smith. 1992. Quantitative subpixel spectral detection of targets in multispectral images. J. Geophys. Res. 97(E2):2659–2672.

Tompkins, S., J.F. Mustard, C.M. Pieters, and D.W. Forsyth. 1997. Optimization of endmembers for spectral mixture analysis. Remote Sens. Environ. 59:472–489.